TensorCodec: Compact Lossy Compression of Tensors without Strong Data Assumptions

Best Student Paper Runner-up


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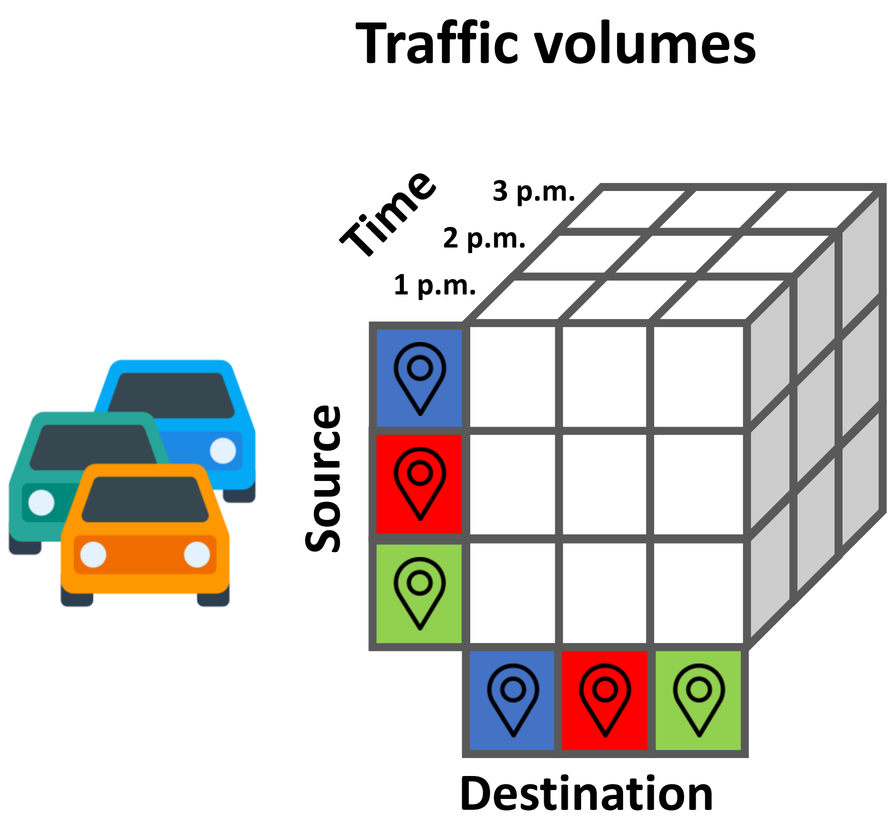
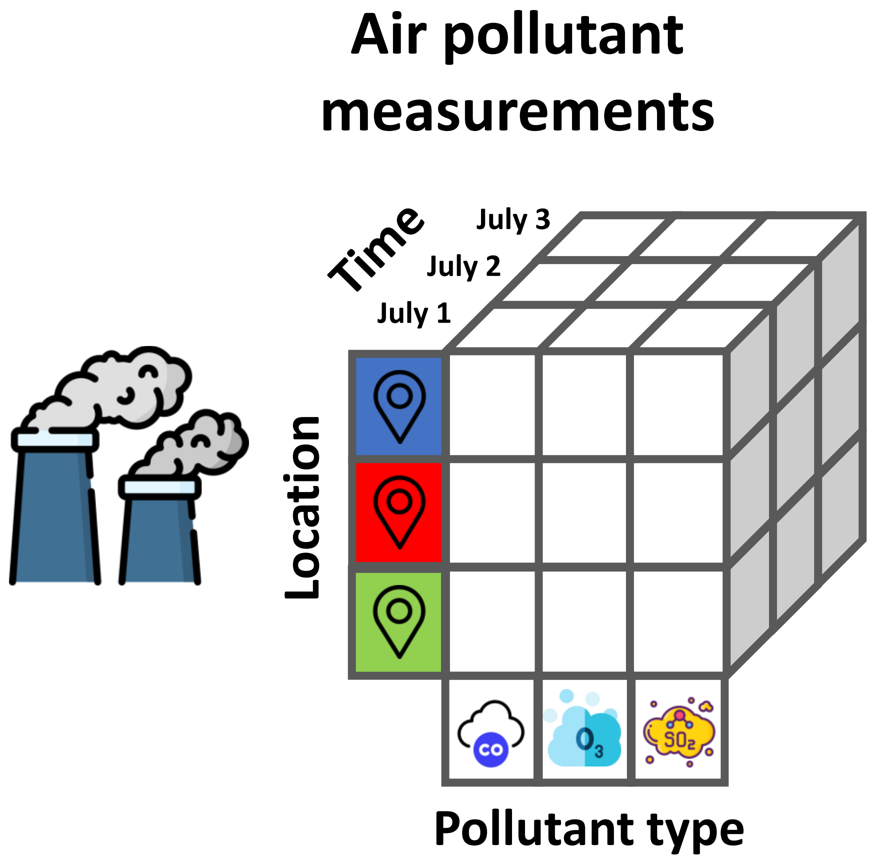
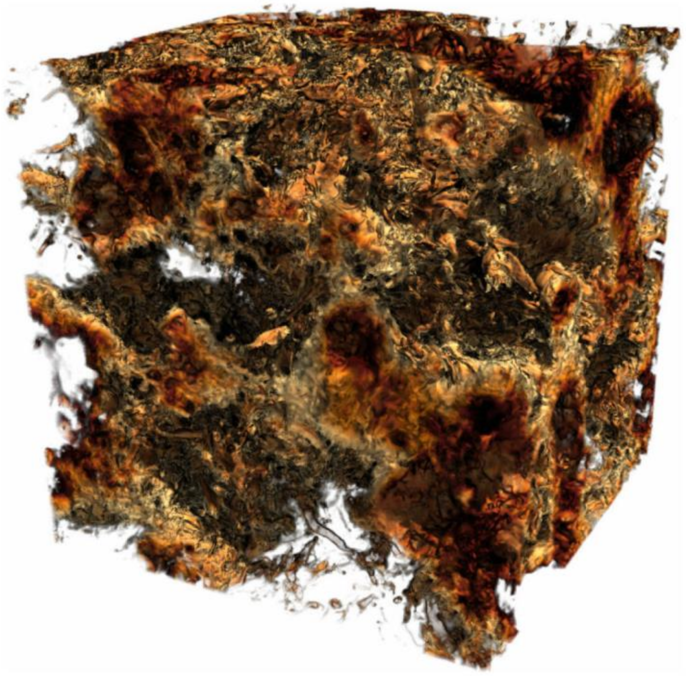
Various data can be expressed as tensors





Why do we need to compress tensors?



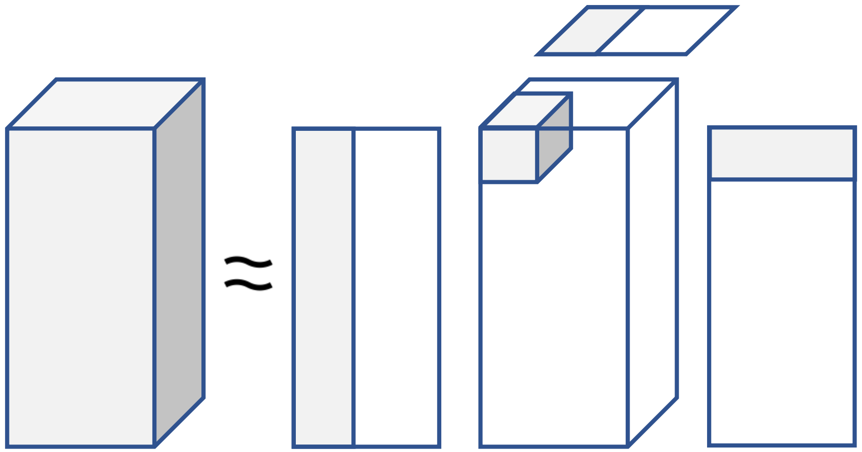
E.g.,) Scientific simulation data

1. Network I/O

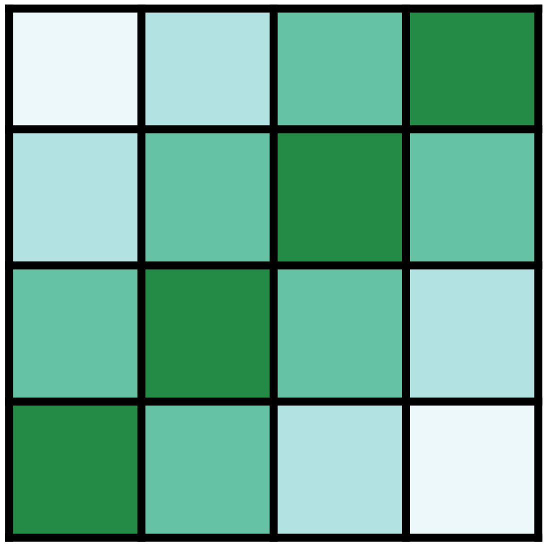
2. Memory requirement

Limitations of existing approaches

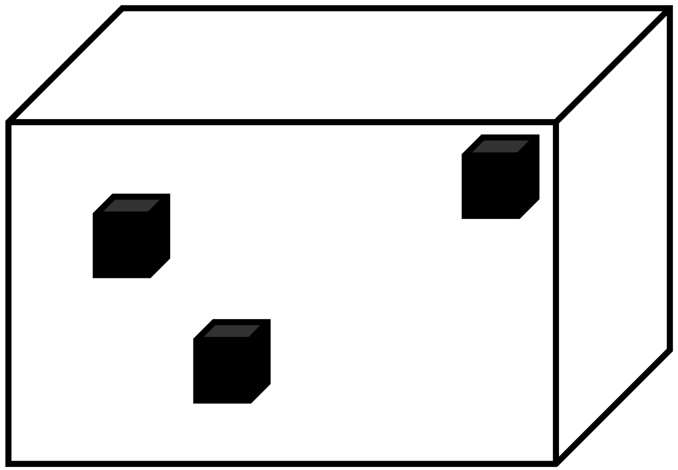
- Existing methods heavily rely on assumptions on input data.



Low-rank structure



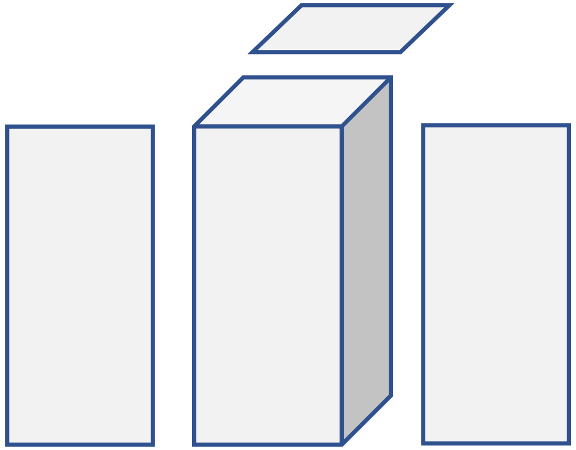
Smooth (e.g., videos)



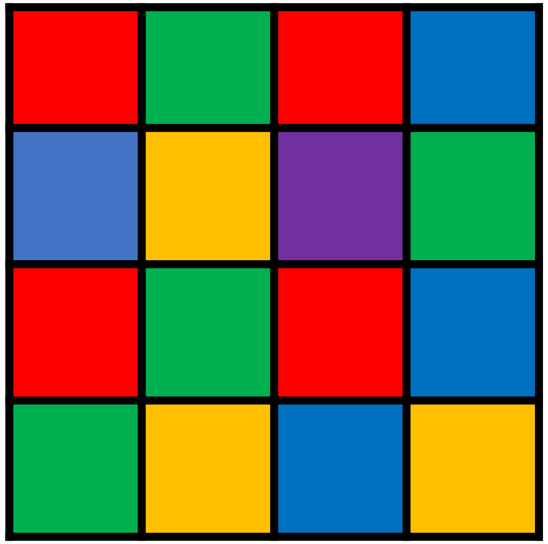
Sparse

Our objective: compression w/o assumptions

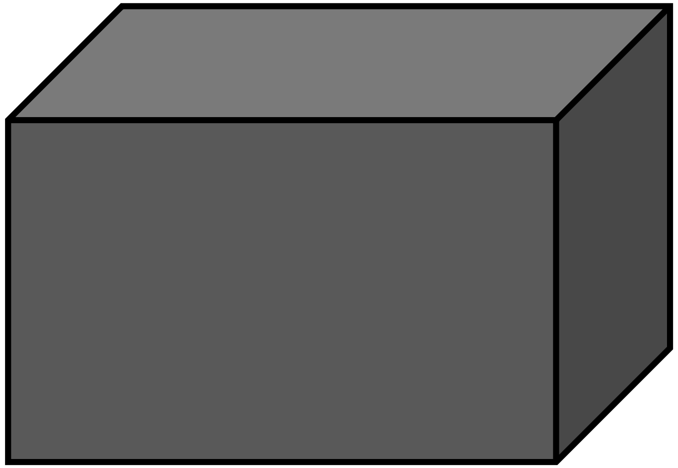
- However, not all real-world tensors meet the assumptions.



High-rank structure



Not smooth

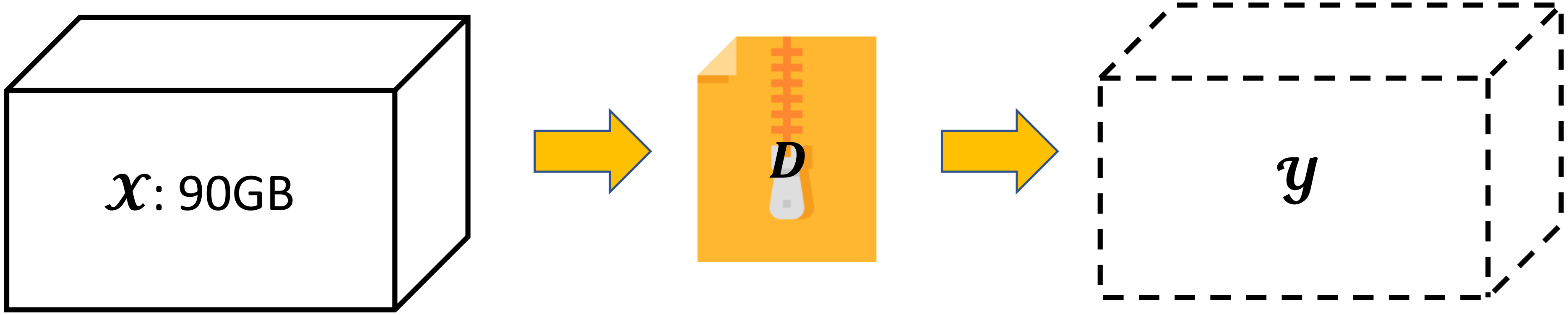


Dense

- How can we compress such general tensors?

Problem definition

Lossy compression of tensors **without** any **data assumption**.



- **Given**: a general tensor $\mathcal{X} \in \mathbb{R}^{N_1 \times \cdots \times N_d}$.
- **Find**: the compressed data D.
- **To minimize**: (1) the size of D and (2) the reconstruction error $||\mathcal{X} - \mathcal{Y}||$

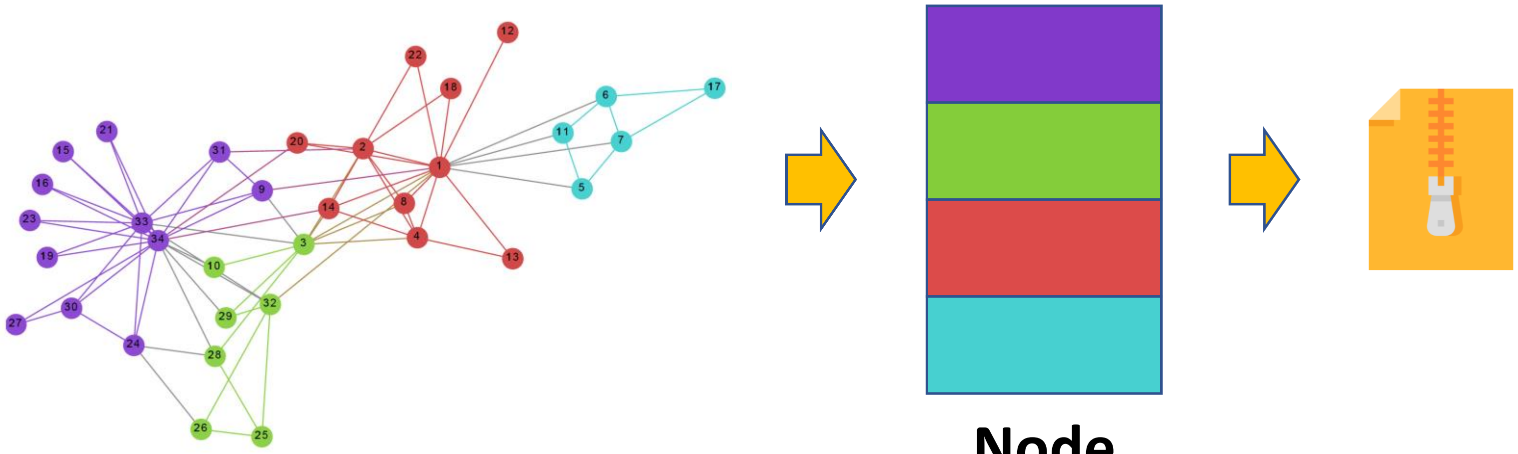
  where $\mathcal{Y}$ is the tensor reconstructed from D.

Outline

1. Introduction.
2. Preliminaries.
3. Proposed method.
4. Experiments.
5. Conclusion.

Tensor-Train decomposition (TTD)

- Our approach is founded on the Tensor-Train decomposition (TTD).
- TTD efficiently compresses large matrices.
  - E.g., Compression of node embeddings for efficiency of GNNs

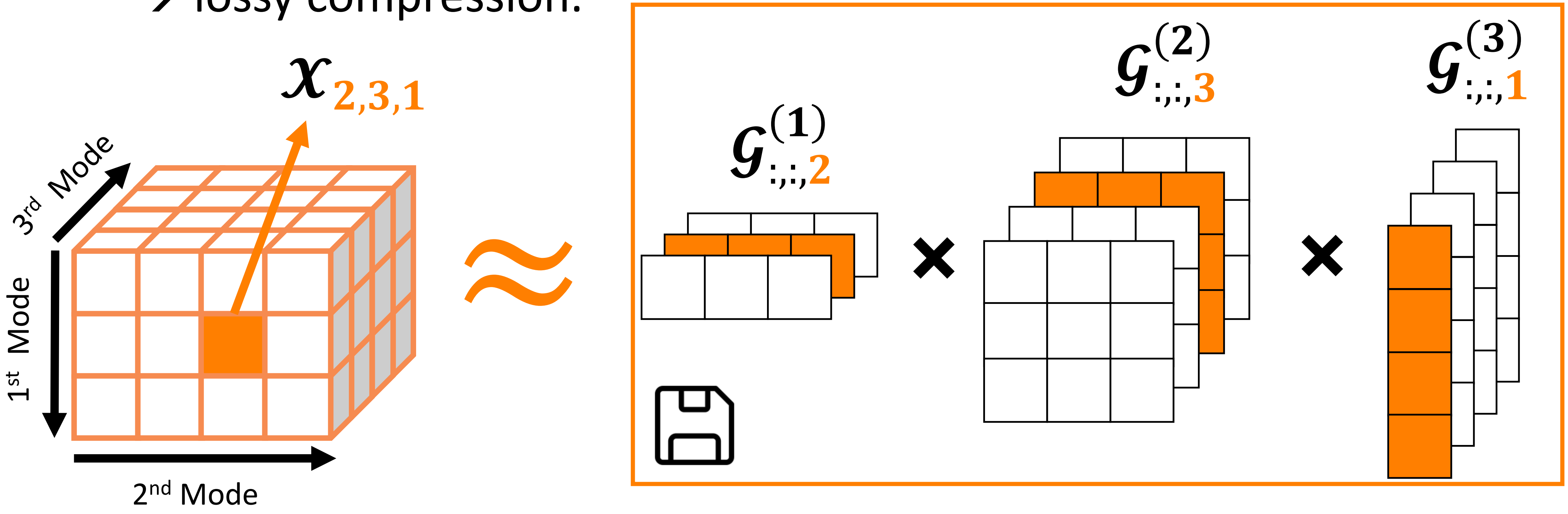


Node embeddings

TTD fitted to node embeddings

Tensor-Train decomposition (TTD)

- TT-cores ($\mathcal{G}$) can be **stored** instead of the input tensor.
- They can be used to **approximately restore** the input tensor.
  → lossy compression.



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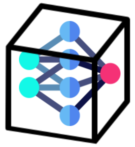
Overview of TensorCodec

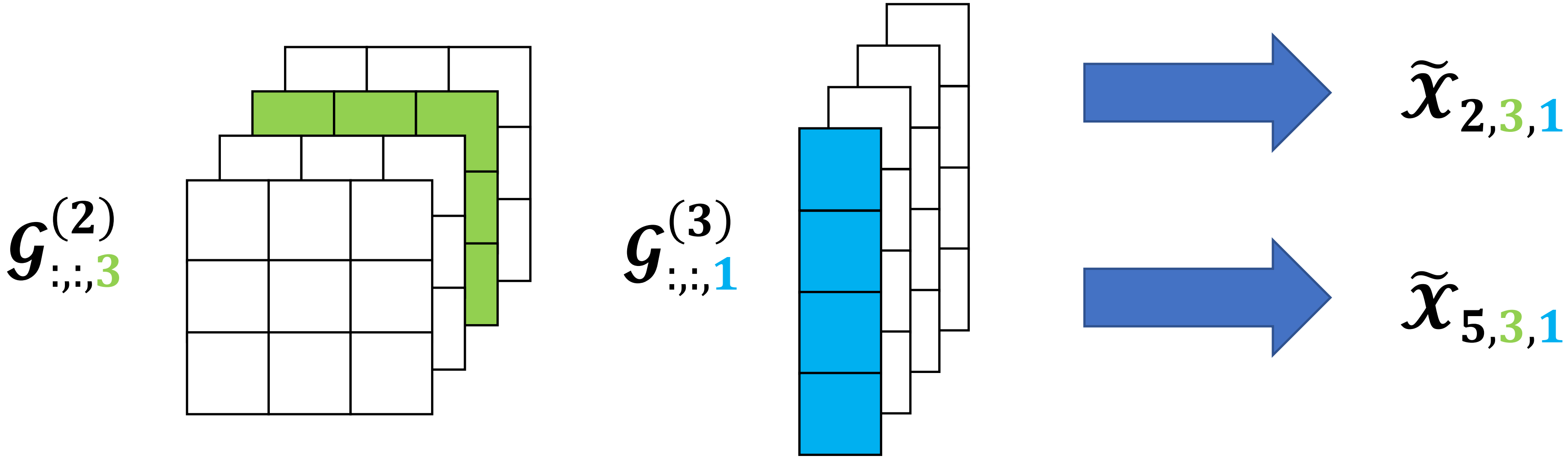
- Our compression algorithm, **TensorCodec**, makes TTD more expressive, concise, and accurate.

- Q1 Expressiveness: How can we enhance the **expressiveness** of TTD?
- Q2 Conciseness: How can we **reduce the parameters** of TTD?
- Q3 Accuracy: How can we **improve approximation accuracy** of TTD?

- **TensorCodec** employs Neural TTD , Folding , and reordering ↑↓

Limited Expressiveness of TTD

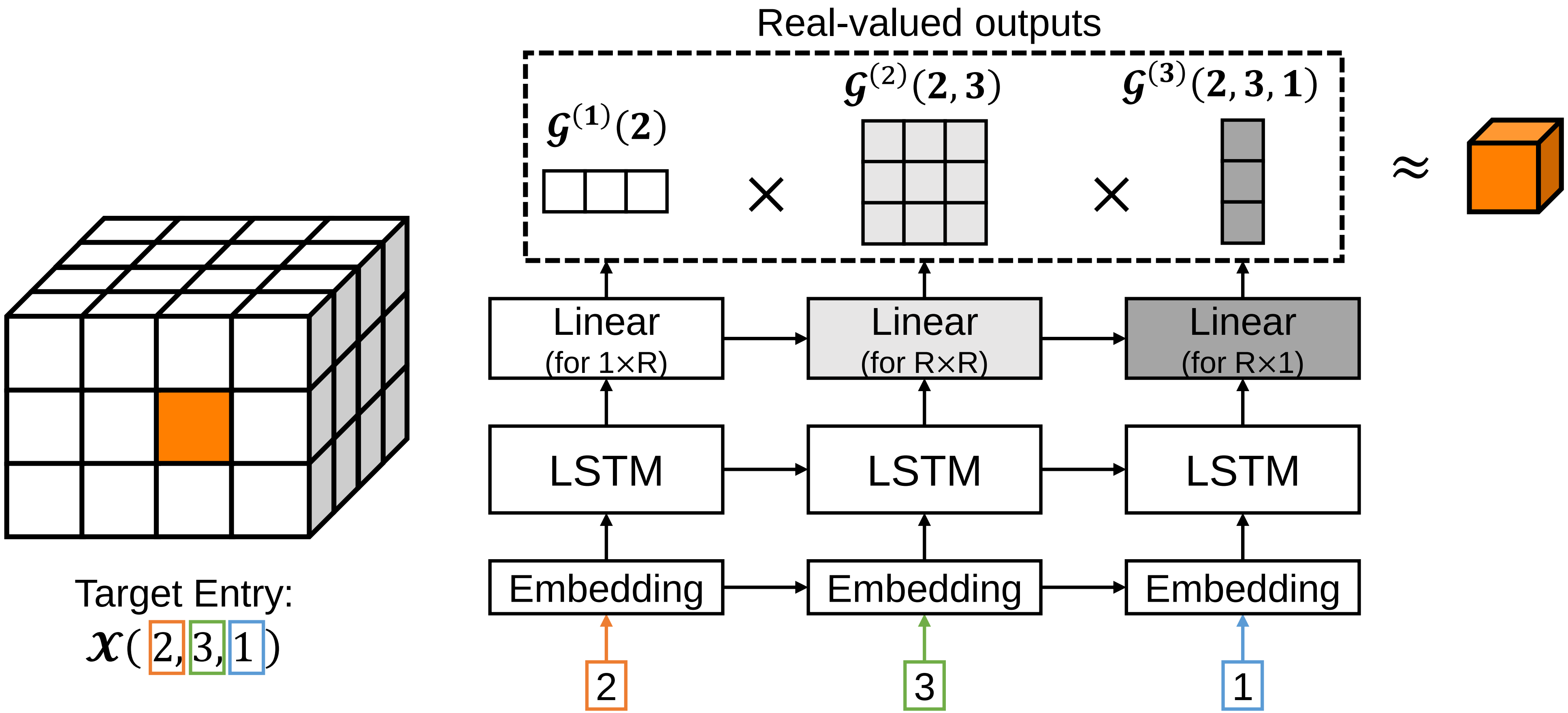
- TT-cores are **fixed** for all tensor entries.



- How can we make TT-cores **adaptive** to each tensor entry?

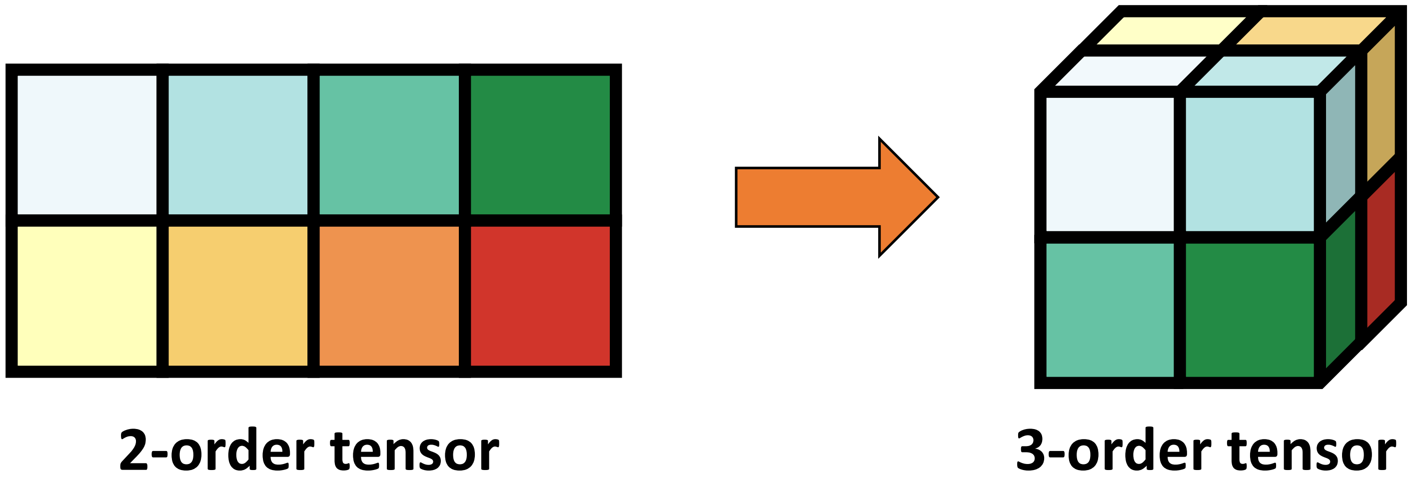
A1. Neural TTD (NTTD)

- We make TT-cores **adaptive** to each entry using LSTM returning TT-cores.



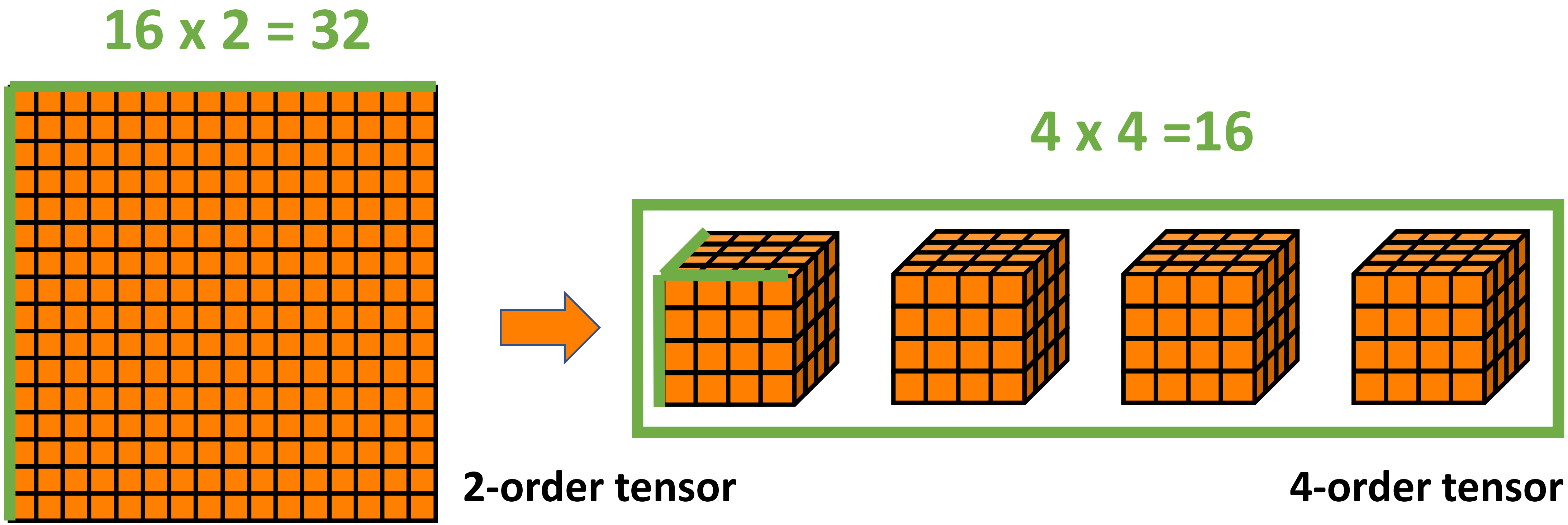
A2. Folding

- **Folding** is the process of mapping each entry of a low-order tensor to an entry of a high-order tensor by splitting dimensions.



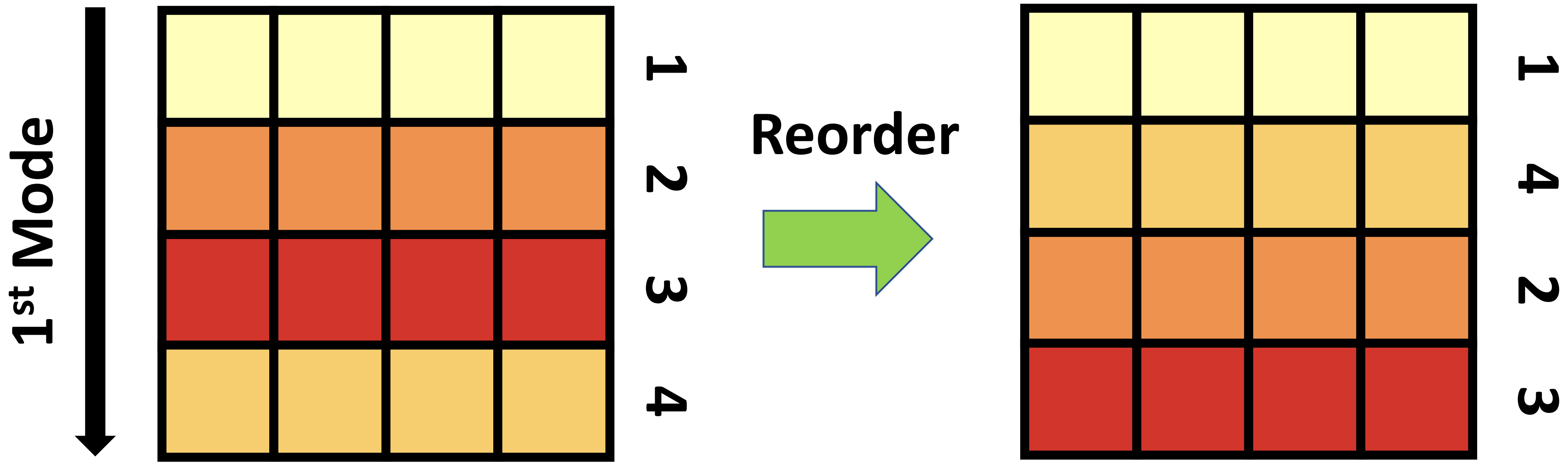
A2. Folding

- The sum of the mode-sizes of a tensor decreases by folding.
- The **number of parameters of NTTD** is proportional to the sum.



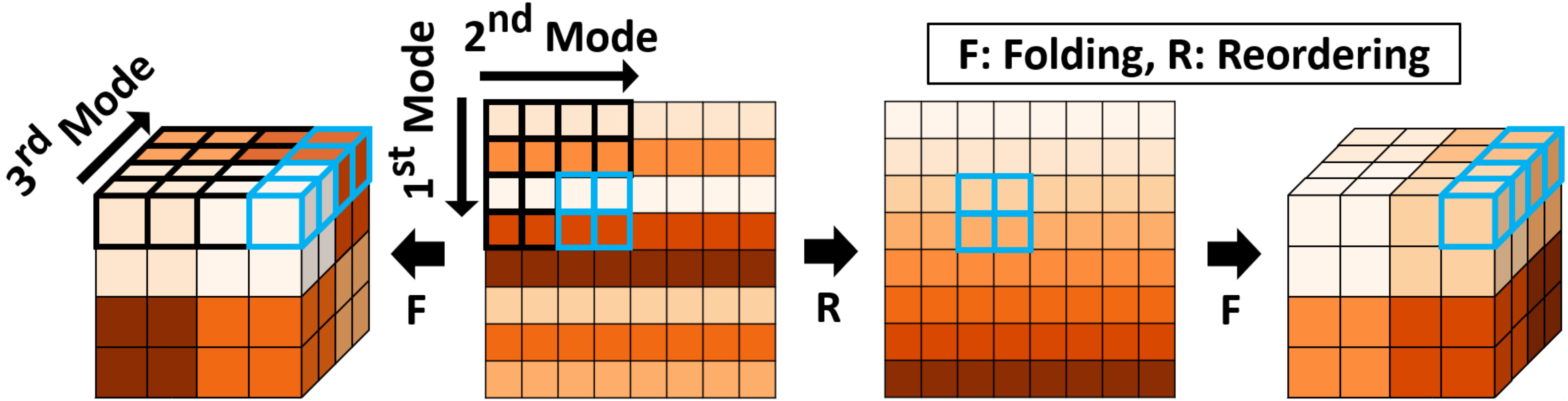
A3. Reordering

- Reordering is the process of changing the orders of indices of all modes so that the similar entries are located nearby.



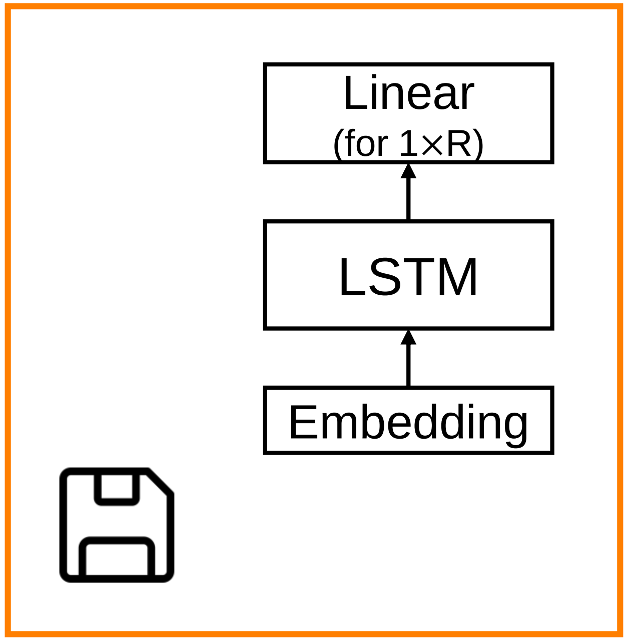
↑↓ A3. Reordering

- The **closer** the entries are in the original tensor, the **closer they are** in the folded tensor.
- **Reordering** helps the model fit the tensor because they share more inputs to LSTM.

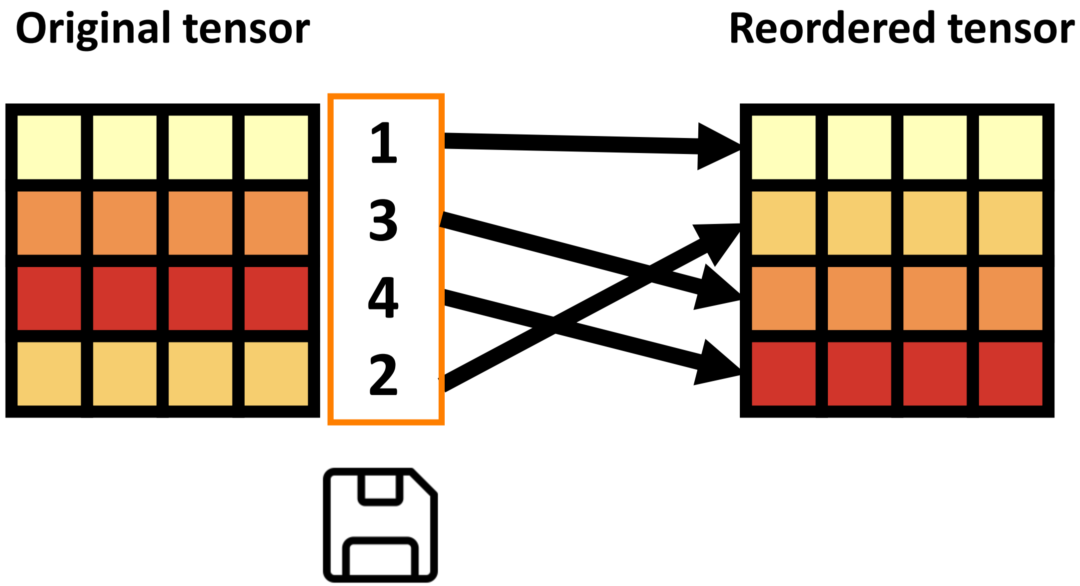


Outputs of TensorCodec

- The **outputs** of compression are (1) **neural-network parameters** and (2) an **index mapping** after reordering

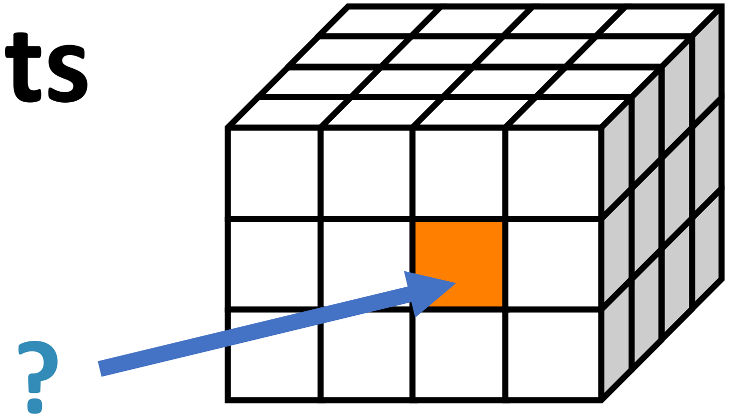


neural network parameters



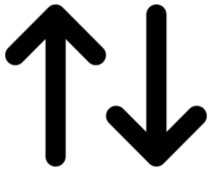
Index mapping

Reconstruction from the outputs



Entry indices
(2, 3, 1)

Reordering

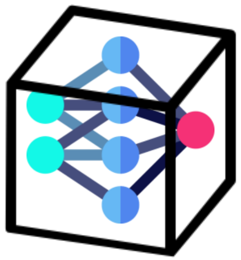


Reordered indices
(12, 23, 2)

Folding

Folded indices
(2, 4, 6, 3, 2)

NTTD



Reconstructed value
2.17

Summary: contributions of each component

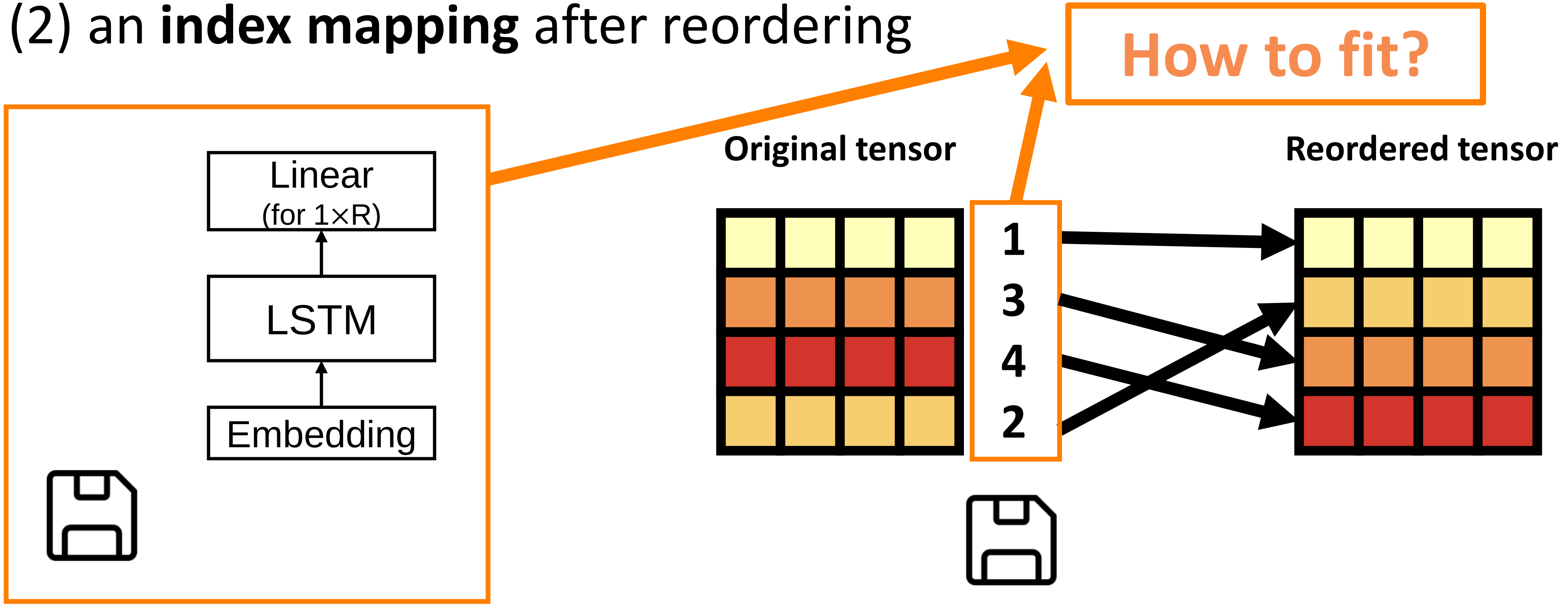
A1. NTTD → **Better Expressiveness of TTD**

A2. Folding → **Better Conciseness of NTTD**

A3. Reordering → **Better Fitness of NTTD** → **Better Accuracy**

Overall training process for fitting the input

- The **outputs** of compression are (1) **neural-network parameters** and (2) an **index mapping** after reordering

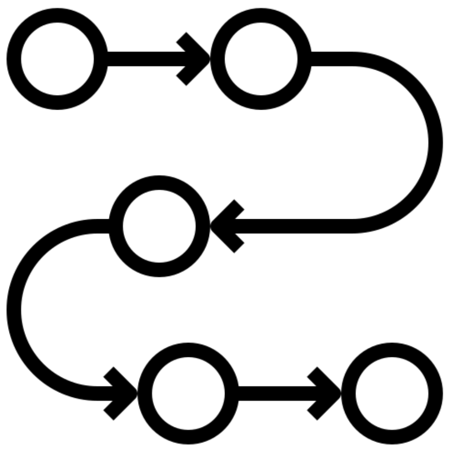


neural network parameters **Index mapping**

Details

Overall training process for fitting the input

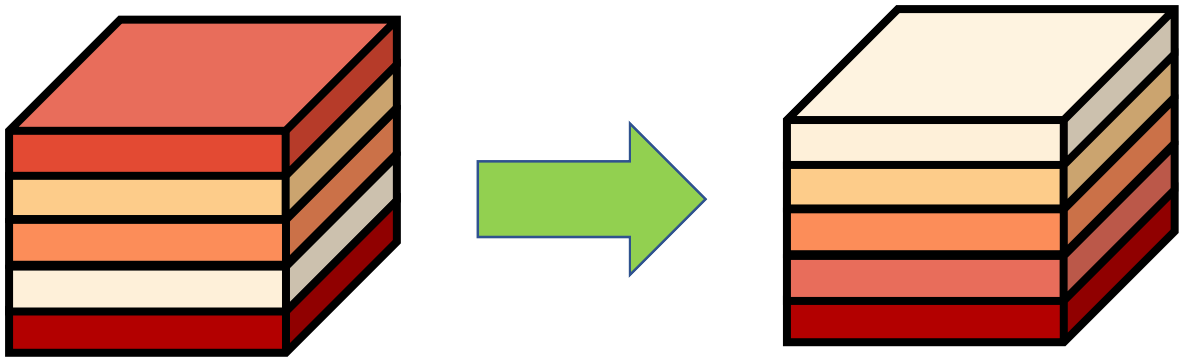
1. Initialize orders (**A3-1**).
2. Update **NTTD** using a **gradient descent**.
3. Update the orders as in (**A3-2**).
4. Repeat 2 and 3 until the error converges.



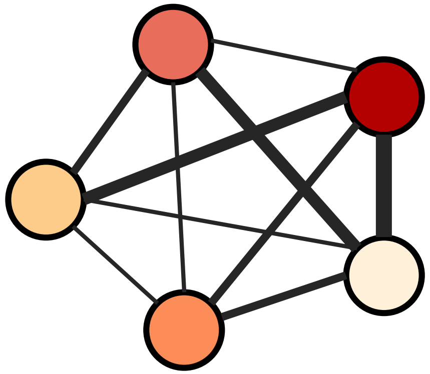
Details

A3-1. Order initialization

- Our goal: minimize the differences between neighboring slices.



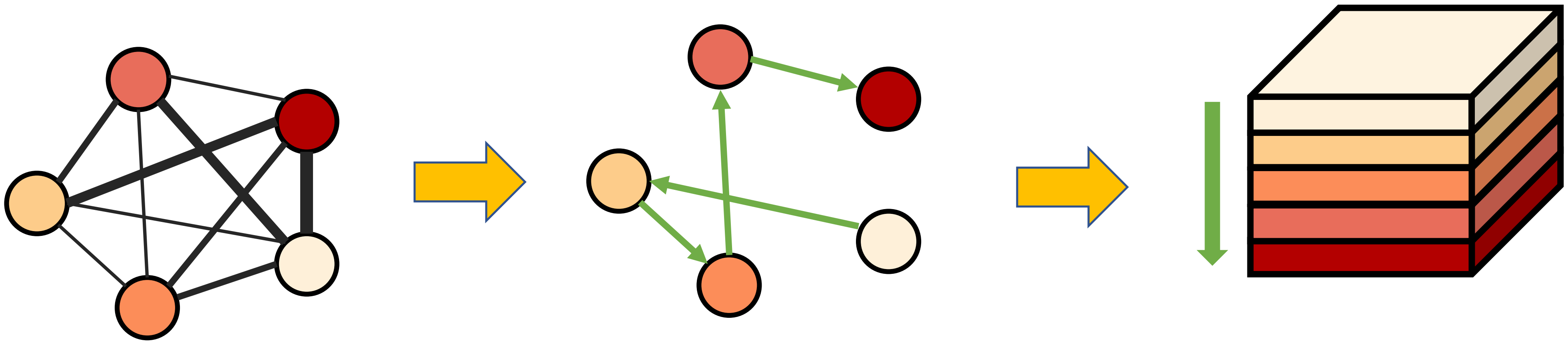
- Consider a **complete graph.**
  - Nodes: slices (i.e., mode indices)
  - Edge weights: L2 distances between the slices.



Details

A3-1. Order initialization

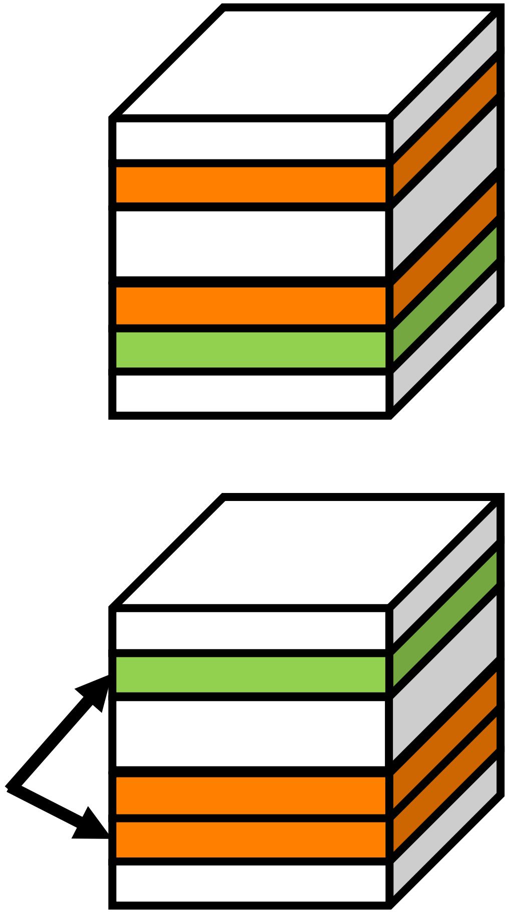
- Find a short cycle with a 2-approximate solution of the TSP.
- Then, remove the largest-weight edge.
- The path becomes the order of slices.



Details

A3-2. Order update using hill climbing

- Finding **similar pairs** of slices using locality-sensitive hashing (LSH) for L2 distance.
- Swap **one slice** with the **neighboring slice of the other** if fitting loss decreases.
- Repeat the above steps.



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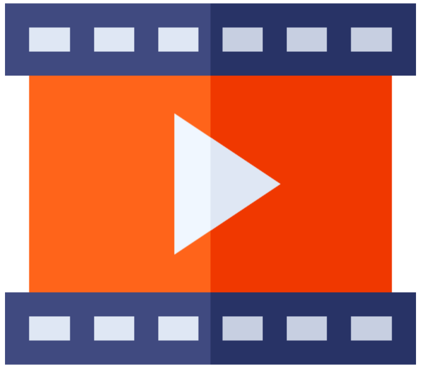
Experimental settings

- Eight real-world datasets: six 3-order tensors and two 4-order tensors.

Air quality measurement

Traffic volume



Video feature

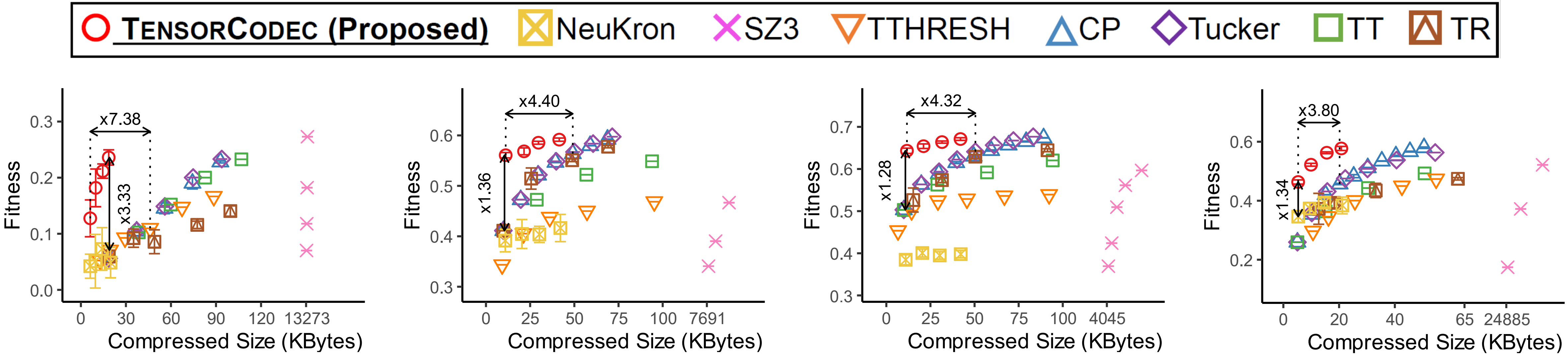
Stock datum

Experimental settings

- Lossy-compression baselines:
  - **Low-rank tensor** compression methods
    - CP, Tucker, TT, and TR decompositions.
  - **Smooth-tensor** compression methods
    - TTHRESH and SZ3.
  - **Sparse-tensor** compression methods
    - NeuKron.

TensorCodec is concise and precise

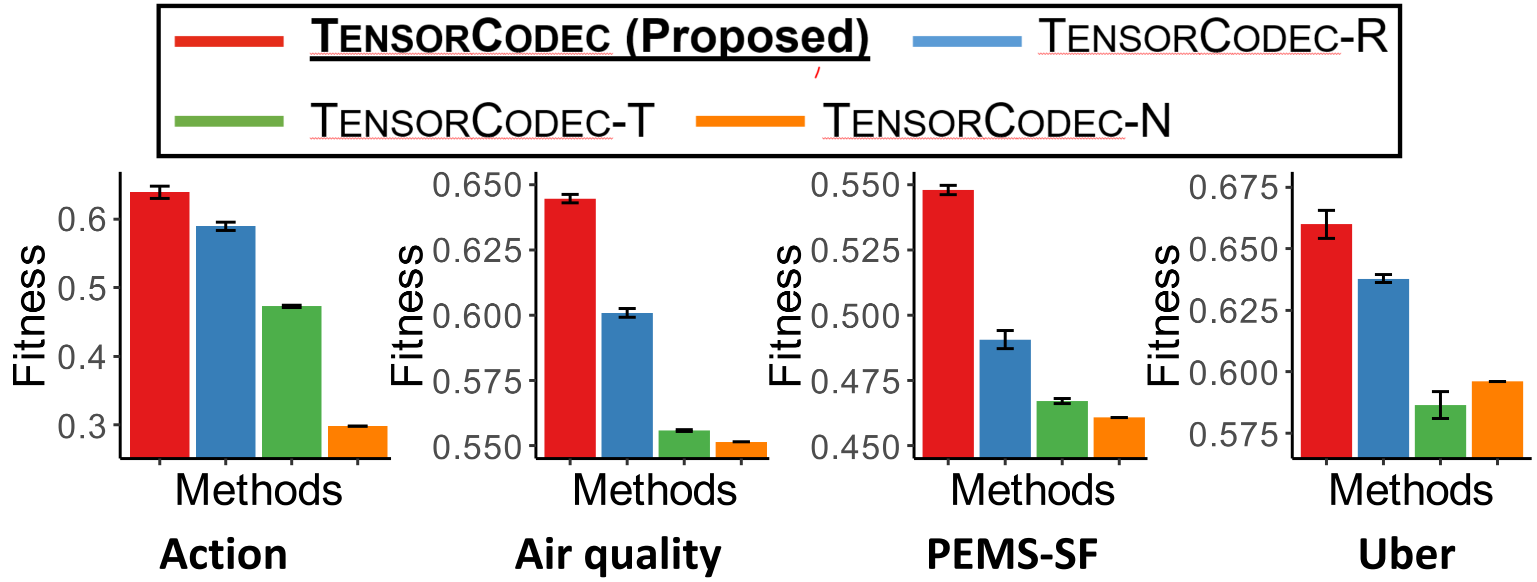
- The compressed outputs of TensorCodec is up to 7.38x smaller.
- TensorCodec shows up to 3.33x better accuracy.



Stock **Activity** **Action** **Absorb**

All components of TensorCodec are useful

- TensorCodec outperforms all of its variants with missing components.



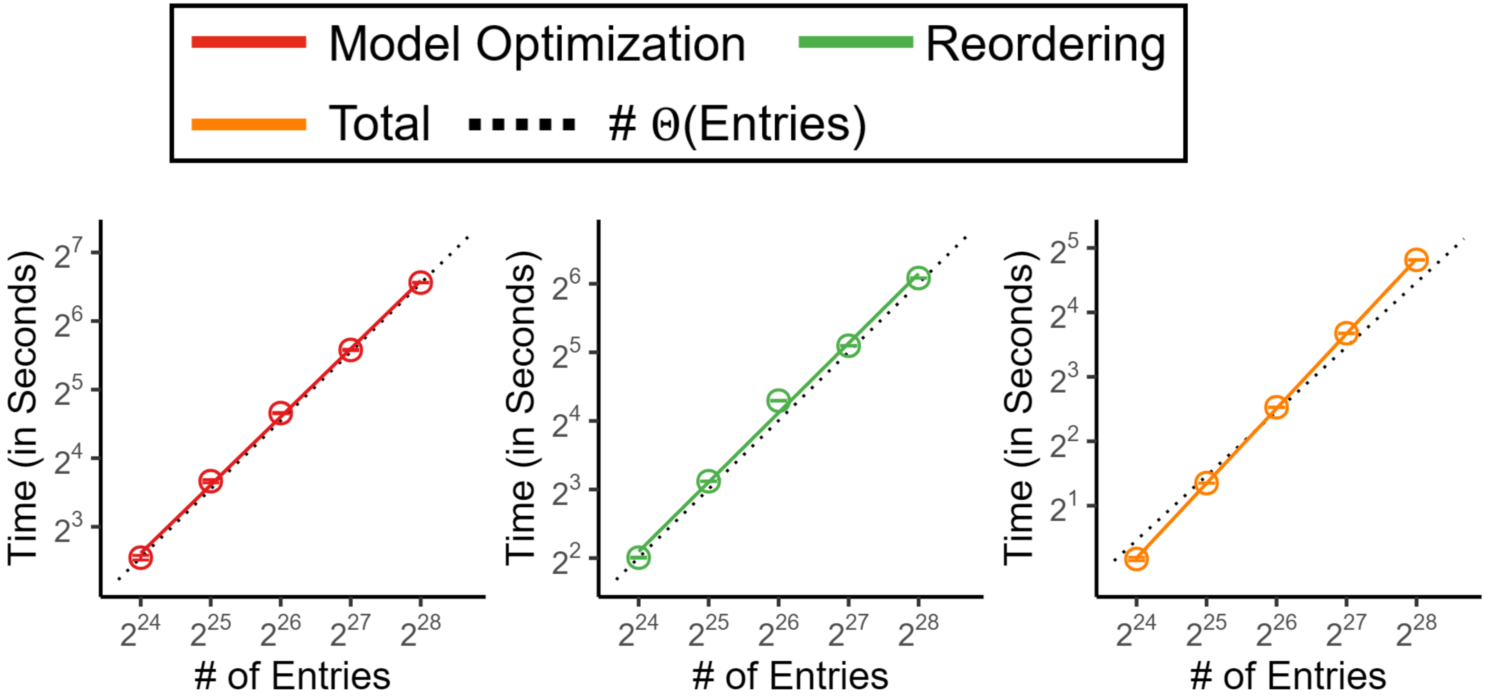
TensorCodec (TC)-R: variant of TC without reordering.

TC-T: variant of TC-R without order initialization.

TC-N: variant of TC-T without a neural network.

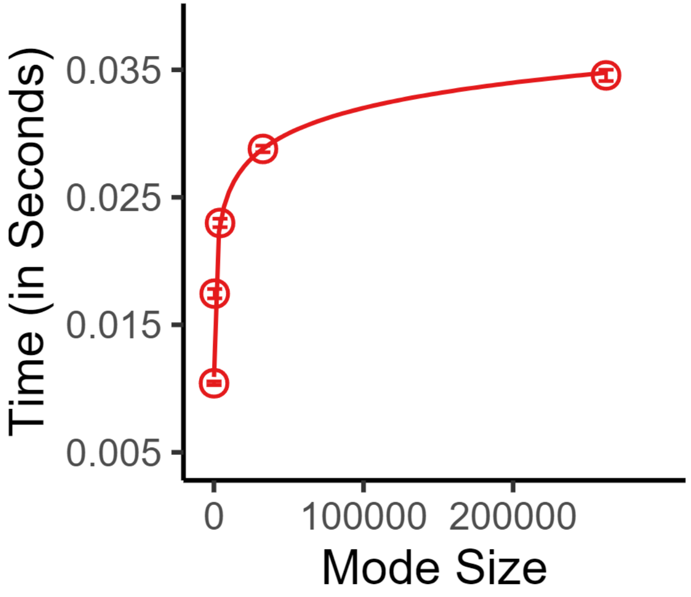
TensorCodec is **scalable**

- Compression time of TensorCodec is linear in the tensor entry count.

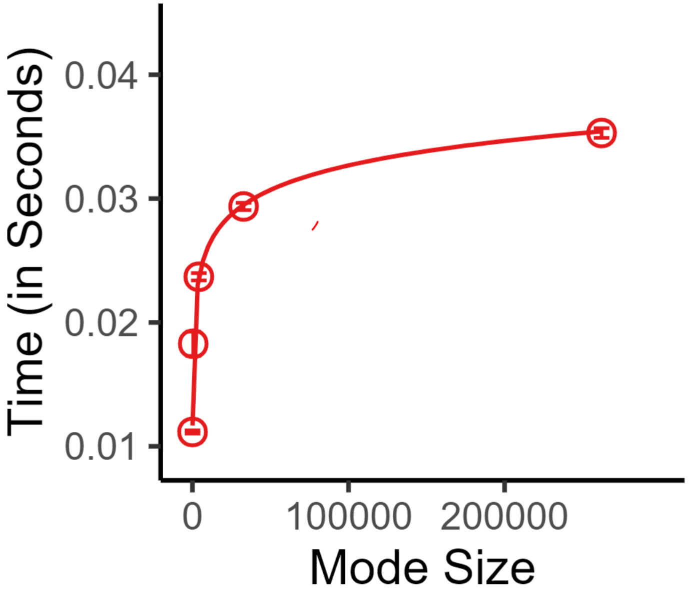


TensorCodec is scalable

- Its reconstruction time is **sub-linear** in the tensor entry count.



3-order tensor



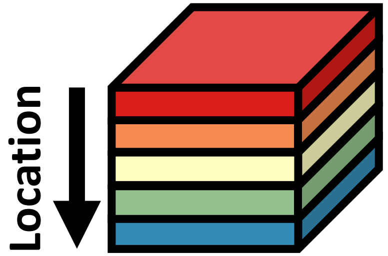
4-order tensor

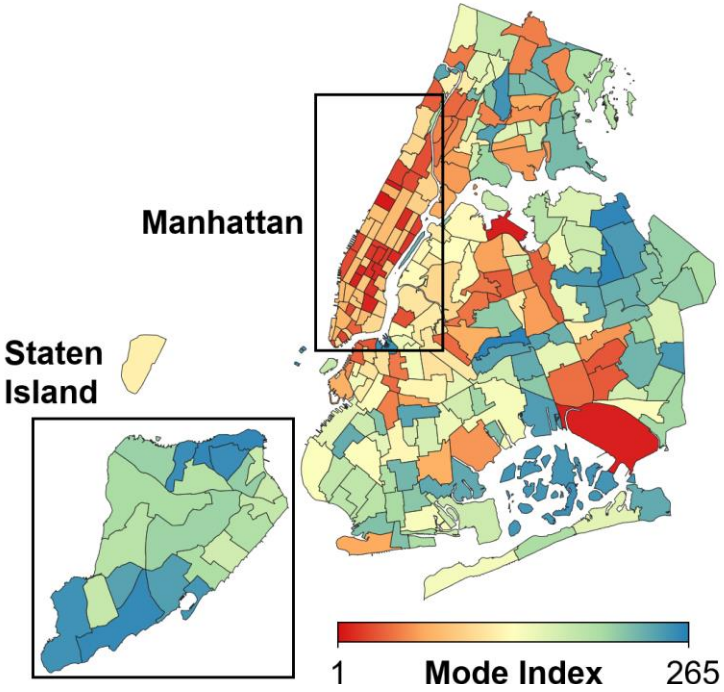
Further Analysis

- Which slices are **closely** ordered by TensorCodec?
- Can TensorCodec approximate **high-rank tensors** with few parameters?

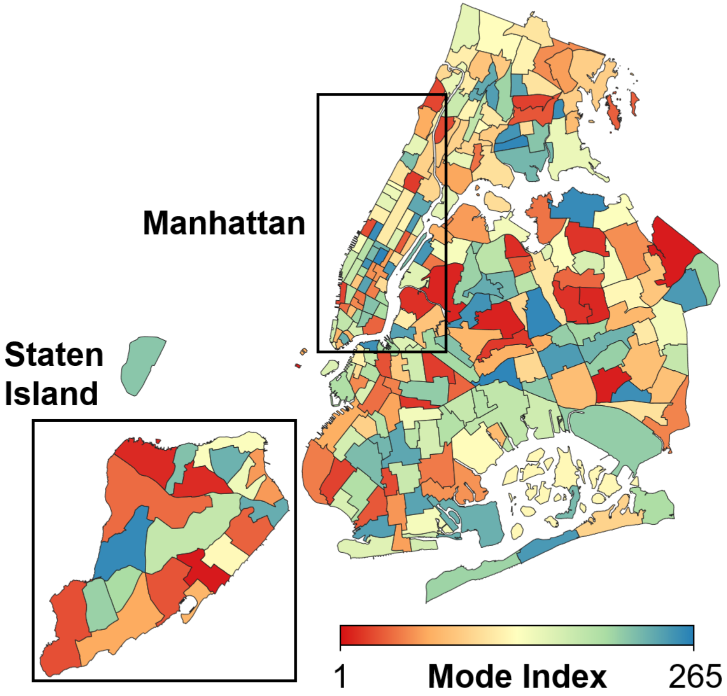
Reordering by TensorCodec is effective

- Reordered results of TensorCodec align with our intuition.





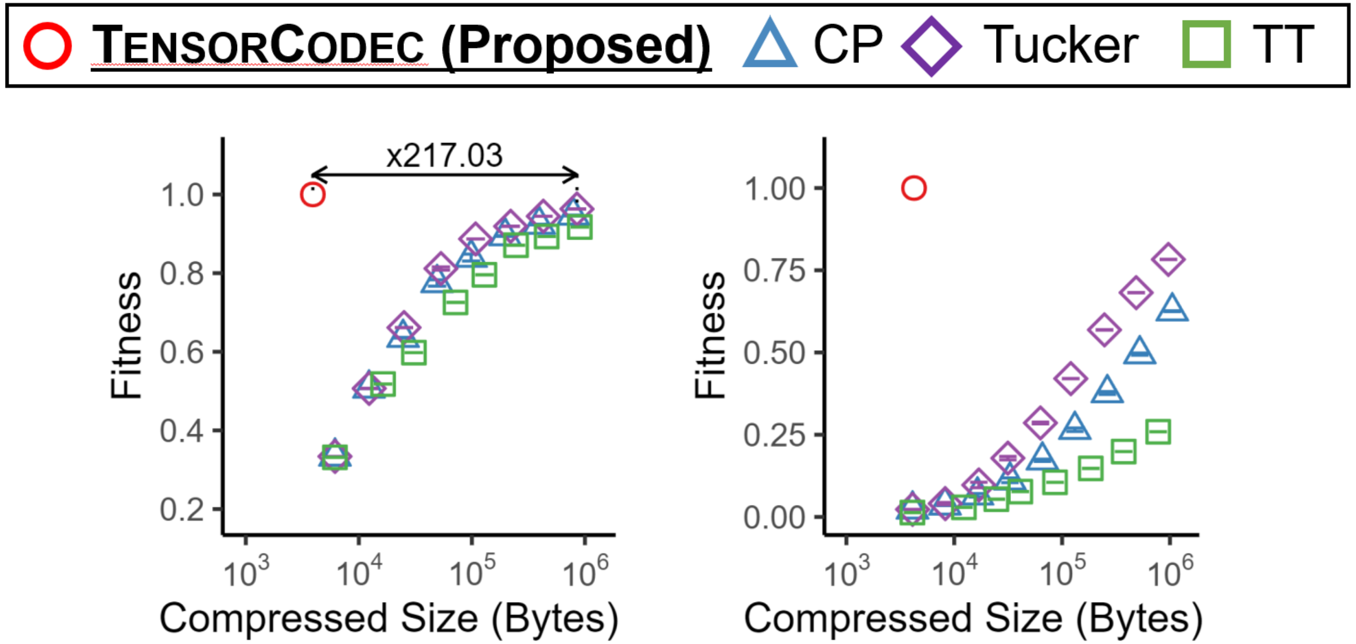
Reordering by TensorCodec



Reordering by NeuKron

TensorCodec is expressive

- TensorCodec fits high-rank tensors with a small number of parameters.



3-order tensor **4-order tensor**

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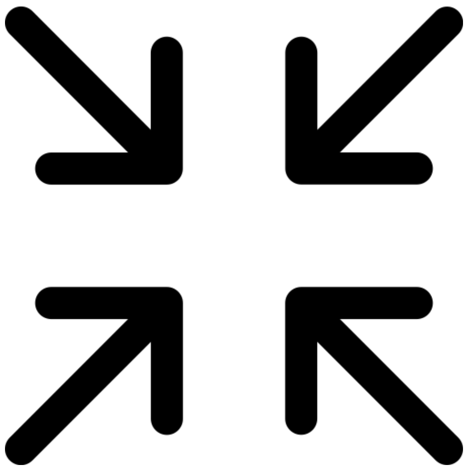
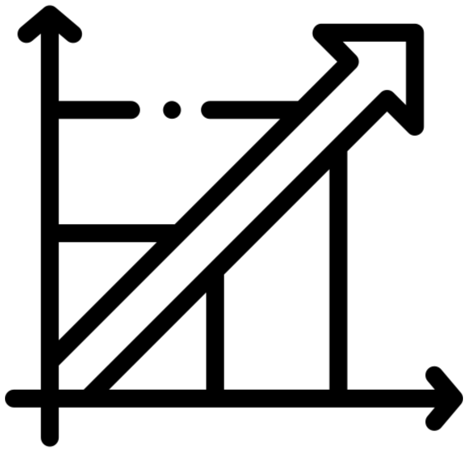
Conclusion

- We propose **TensorCodec** for **lossy compression** of general tensors.
- **TensorCodec** is **concise**, **accurate**, and **scalable**.



Concise

Accurate



Scalable

Thank you for listening!

Any question?

Code & Datasets: https://github.com/kbrother/TensorCodec